

Article

On Spatially Dependent Risk Preferences: The Case of Nigerian Farmers

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Abstract: Rice farmers' attitudes toward risk-taking have been identified as one of the factors affecting investment decisions and wealth accumulation. While existing studies have identified the socio-economic factors driving farmers' risk attitudes, spatial variables that may correlate with decisions are often ignored in the risk models due to difficulties in measurement. We studied unobserved spatial heterogeneity in farmer's risk preferences by incorporating spatial dependency into a farmer's risk preference model. We used data from a survey conducted with Nigerian farmers between March and May 2016. The survey collected information on 2016 farmers' socio-demographic characteristics and farm attributes including its geographical location as well as information on the quality of roads. In addition, a set of experiments design to elicit farmers' attitudes toward risk were conducted. We estimated a spatial autoregressive model using the instrumental variable method. We found that unobserved spatial heterogeneity (e.g., soil, topographic farmers emulating each other) was present in farmer's risk preferences along with socio-demographic variables such as age, gender, marital status, and religion and farm characteristics such as farm size and road quality. These results are relevant for policy decision-making processes.

Keywords: decision making; instrumental variable; neighbourhood effects; rice farmers; risk attitudes; spatial dependence



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1. Introduction

Farmers' adoption of agricultural practices and technologies that contribute to achieving sustainable intensification, sustainable development, and food security require some degree of risk taking and risk management by farmers. Farmers face climatic shock risks (e.g., flood, drought) and pest and disease risks, as well as market input and output price fluctuations [1]. In addition, the inadequate access to insurance and other risk mitigation strategies by smallholder farmers in developing countries means that risks associated with agricultural production are relatively important in their decision-making process. Despite smallholder farmers usually being thought to have homogeneous risk averse attitudes [2], there is evidence that this is not the case. Hence, identifying and understanding the heterogeneity in farmers' risk preferences is crucial to guide policy formulation and implementation on risk management and investment decisions (e.g., technology, the adoption of new crop varieties, or the adoption of sustainable agricultural practices). However, few studies have analysed heterogeneity in risk preferences [3–11]. Institutional and non-institutional factors have been associated with farmers' risk attitudes [12–16]. Importantly, farmer's risk preferences may be associated with the climatic, soil, topographic,

and economic conditions of the farm's geographic location and the farmer's economic situation. For instance, farmers in the coastal areas of Vietnam are reportedly less risk averse than farmers in non-coastal areas [14,15,17]. Additionally, a negative correlation is reported between low rainfall areas and farmers' risk aversion in Uganda [16]. Farmers' risk preferences may also be influenced by the risk preferences of other farmers who are in geographical proximity, or by the availability or otherwise of infrastructural or institutional facilities such as roads, schools, and markets [18]. For example, neighbourhood effects are observed in farmers' agricultural technology adoption patterns [19–23], partly because culturally, farmers living closely often rely on their friends and neighbours to acquire and share information on improved farm practices. The social composition of farmers may reveal neighbourhood effects [24]. Such an influence may lie within or extend beyond the current agricultural zones/land divisions. The degree of heterogeneity in farmer's risk preferences may therefore reflect the existing economic reality of farmers within and across agricultural zones in Nigeria.

Hence, there may be the presence of spatial unobserved heterogeneity when analysing farmer's risk preferences. Ignoring this spatial unobserved heterogeneity in farmers' risk preference models may lead to biased coefficient estimates [25–29]. Despite advances in the spatial econometrics [30,31], there is no attempt to examine the role of spatial dependence in risk preference.

The aim of this paper is to investigate how unobserved spatial heterogeneity in farmers' risk preferences may affect farmers' risk preferences. We investigate the heterogeneity of farmer's risk preferences (i.e., the extent to which a decision maker (DM thereafter) is willing to take risky decisions [32,33]) and the determinants of these preferences by incorporating spatial unobserved heterogeneity into a farmer's risk preference model along with farm- and farmer-specific factors (age, education, religious beliefs, household size, farm size, gender, marital status) and infrastructure quality (bad roads). Our approach differs from past studies in terms of the elicitation method used in this setting. We hypothesize that rice farmers' risk preferences are spatially dependent, a novel hypothesis in the field of agricultural and applied economics. That is, farmers living closely have similar risk attitudes relative to distant ones due to spatially determined conditions.

2. Materials and Methods

2.1. The Theoretical Model

A structural autoregressive (SAR) model was employed to account for spatial heterogeneity in risk preferences in line with past studies [25–27]. The application of a spatial model is driven by the nature of the data and theory [30,31]. Spatial dependence is a tendency for random variables to correlate with one another due to geographical proximity. It is hypothesized that the observed variation in DM risk preferences may be associated with spatially unobserved conditions such as infrastructure, cultural values, climatic conditions, etc. These are accounted for through an SAR model where the association between the distance-weighted average of neighbouring DM's willingness to take risks and the DM's own willingness to take risks can be investigated. Equation (1) is based on the assumption that the DM maximizes the payoff or expected payoff in the panel risk lotteries. Panel lotteries with four treatments are applied in this study. Detailed formulations are presented in the data sub-section. The treatments are defined as small gain one (SG_1), small gain two (SG_2), large gain one (LG_1), and large gain two (LG_2) to capture heterogeneity in risk preferences.

$$\text{Max } U(y_i, y_j; X) \quad (1)$$

where U is a utility function, y_i represents the utility derived by a DM from the lottery in location i , y_j implies the utility derived by the DM from the lottery in location j , and X is the vector of farmers' exogenous (and endogenous) socio-economic variables. The maximization objective produces a spatial reaction function, $y_i = F(y_{ij}, X)$ which forms the SAR (Equation (3)). This captures the dependency between the observational units [34]. The data generating process (DGP) reveals a global spillover, since $(I - \rho W)^{-1}$ links y_i

to all X through a multiplier, the spatial weights matrix (W). The power weights matrix adopted from Roe, Irwin and Sharp [18] is shown in Equation (2). This is adapted from Areal, Balcombe and Tiffin [28]. The distance based power weights function has many advantages. First, unlike the binary contiguity method, neighbours may be assigned with different weights. Second, more weights are attached to shorter distances, implying that the closer proximity the neighbours are, the more the influence. In other words, the weights are closer to one when the distance (d) is less than the cut-off distance (s), but tend towards zero when the distance is greater than the cut-off distance. In addition, assuming an equal number of neighbours may be inappropriate, since the number of sampled farmers is not equal across all locations or agricultural zones.

$$W_{ij} = \exp(-d_{ij}^2/s^2) \quad (2)$$

where d_{ij} is the distance between DM in locations i and j , estimated from the recorded farmers' GPS coordinates (latitude and longitude), s is the cut-off distance that sets the spatial dependency limit distance after which the spatial effect is decreasing at a slower pace. Different cut-off distances were tested to determine the limit of spatial dependence in line with past studies [18,28,29]. W is often row-standardized, in which the sum of each row of the matrix equals one to facilitate the interpretation of the spatial coefficient results [19,22,24]. Only the diagonal elements of the weights matrix are set to zero to prevent rice farmers from being a neighbour to themselves.

$$y_r = \rho W y_r + X\beta + \varepsilon \quad (3)$$

In Equation (3), y_r is a column vector of willingness towards risk taking (risk avoidance is used interchangeably with willingness towards risk taking to refer to risk aversion because the parameter of the curvature of the utility function is not estimated. This is because risk preference has been previously defined as the extent to which an individual is willing to take risky decisions [2]). This is a probability index corresponding to farmers' choices in the panel lotteries and it ranges between 0 and 1 with an index of 1 indicating being highly unwilling to take risks. The ρ measures the strength of spatial dependence or spatial correlation between the risk preference of a DM and the adjusted-by-distance mean risk preference of their neighbours. W is the $N \times N$ weights matrix (Equation (2)). X is the $N \times K$ vector of exogenous explanatory variables. β is a $K \times 1$ vector of estimated parameters. $W y_r$ is a spatial lag, which is the weighted average of risk willingness in the neighbourhood locations. The disturbance term is assumed to be independently and identically distributed, $\varepsilon \sim N(0, I\sigma^2)$. The rho (ρ) is not restricted between -1 and 1 [35]. This suggests that it cannot be linearly interpreted as a conventional correlation between decision makers' willingness to take risks (y_r) and the adjusted-by-distance willingness to take risks of the neighbours ($W y_r$). Equation (3) also suggests that the expected value of DM willingness to take risks, y_r , depends on $X\beta$ plus the neighbouring values of DM scaled by the dependence parameter, ρ .

The potential endogenous problem of spatial lag variables (the correlation between the spatial lag (W) and the disturbance error, ε) is addressed using the instrumental variable (IV) method. The application of IV requires the choice of an instrument, Z , which must satisfy two conditions. First, an instrument must be exogenous, which may be mathematically represented as $Cov = 0$. Second, an instrument must correlate with the endogenous explanatory variable (that is relevant), $Cov \neq 0$. Thus, X are assumed to be exogenous variables, and we use as an instrument the spatial lag of education, $Weducation$.

We used the R package ivreg [36] to estimate the model in Equation (3) using an instrument variable regression where the instrumental variable used is $Weducation$. The R package provides three different tests to ascertain the relevance of the instruments, the endogenous nature of an explanatory variable, and the validity of the instrument. The test of instrument relevance involves examining the significant of the Wald statistic. The Wu–Hausman test, a test of restriction, was adopted to test the endogenous nature of the

spatial lag variables. This test is important since IV may produce estimates with larger standard errors relative to OLS if the spatial lag variable is not endogenous. Thus, it is referred to as the test of the consistency of OLS. Lastly, the test of validity of the instrument, often called the Sargan test. This tests over-identification restriction, but is not usually reported in an exactly identified model.

As part of the explanatory variables, we considered farm and farmer characteristics, as well as the quality of the infrastructure around the farm (road quality). We accounted for farm size, which can be a proxy for income in developing countries where livelihoods largely depend on farming. Studies from Ethiopia showed that farm size and risk aversion were negatively correlated [8] and positively related [5], although some studies found no significant relationship [10,37]. We included the farmer's level of education as an explanatory variable for farmer's risk preferences. The direction of the relationship between education and risk preferences has been mixed. Educated farmers are reported as showing aversion to risk taking in developing countries [10,15,38]. However, a positive relationship was also reported between risk aversion and education in Southern Peru [39] and West Africa [40]. The farmer's age was also considered as an explanatory variable for farmer's risk preferences. Research showed that younger farmers are less risk averse [9,15], while others indicated that older farmers are more risk averse [10,40]. The debate on whether women are more risk averse relative to men is inconclusive. For example, Schubert [41] found contrary results when compared to studies that provided strong statistical evidence that males are less averse to risk. In finance and investment, for instance, women are less financially tolerant and more financially risk averse compared to men [42–44]. On the other hand, Harris, Jenkins and Glaser [45] attributed the gender differences in perceptions about outcomes and risky decision making to less desire for enjoyment among women. Research also shows that the social status of individuals may drive risk aversion [46]. Although results on gender have been mixed, in agricultural settings, women are reported to be more risk averse than men [16,37,47]. Consequently, we have included gender as an explanatory variable in the analysis. Marital status was also included as an explanatory variable since it is important in a farmer's decision making process. On one hand, married individuals may be risk takers to cope with the financial burden. On the other hand, they may be more risk averse than the singles because of the fear of income loss when under intense financial pressure. Another variable that has received less attention in the literature is a farmer's religious beliefs. Religious farmers were found to be more risk averse than non-religious people, although it is difficult to know the degree of how risk averse religious people are [37]. Since religion relates to belief, it may affect farmers' perceptions and risk preferences. Notwithstanding, there is no expectation on the direction of this variable. Like other variables, mixed results have been reported between risk aversion and family size. For example, Liebenehm and Waibel [40] reported a positive correlation in West Africa. Large family sizes may prompt action towards taking risky decisions. Thus, farmers with a large family size are expected to be more willing to take risky decisions.

2.2. Source of Data

This study used experimental and survey data collected between March and May 2016 from Ogun State Nigeria. Following Binswanga [3,4], a number of studies have experimentally examined farmers' risk attitudes using different methods. As earlier stressed, the term risk avoidance is introduced in place of risk aversion to refer to an individual farmer who is strongly less willing to take risky decisions since the parameter of the curvature of the utility function is not estimated. The DM's risk preferences were elicited using panel lotteries originally proposed by [48], given the name S-GG. The S-GG has been applied in different contexts and countries, but we follow the specifications in [49], with modifications to the nomenclatures. Other applications of this risk attitude elicitation method can be found in some European studies [50,51]. The panel lotteries have four treatments each, with the nomenclature being small gain one (SG_1), small gain two (SG_2), large gain one (LG_1), and large gain two (LG_2). Each treatment has four panels each. A recently published working

paper highlighted the advantages and limitations of this risk elicitation method [52]. One unique feature of the panel lottery is that each panel has ten separate lotteries from which the DM chooses one option. We adapted the original S-GG lottery that was presented in Euro to Naira with an exchange rate of 1 Euro to 225 Naira in 2016. Most risk preference elicitation methods in the literature are categorized into laboratory or field, but our risk experiment belongs to lab experiments in the field [2,53].

For SG_1 (and other stakes), DM is faced with a probability (P) to win a payoff (X), or nothing otherwise. Both the payoffs and the probabilities vary across the rows in each panel. Note that the probabilities are the same for each panel of each treatment. The payoffs increase while the probability associated with winning a reward decreases as we move from row (option) one to row (option) ten. The panel lotteries have four treatments with four panels each. The summary of the payoffs is presented in Table 1.

Table 1. Panel lotteries' payoffs.

Panel Lotteries for Four Treatments (Currency in Naira)										
P	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
$X (SG_1)$										
Panel 1	225	251	282	322	376	451	563	751	1126	2251
Panel 2	225	251	282	322	376	451	564	753	1129	2259
Panel 3	225	251	283	324	379	455	570	762	1145	2295
Panel 4	225	252	284	326	382	460	578	774	1165	2340
$X (SG_2)$										
Panel 1	0	26	57	97	151	226	338	526	901	2026
Panel 2	0	26	57	97	151	226	339	528	904	2034
Panel 3	0	26	58	99	154	230	345	537	920	2070
Panel 4	0	27	59	101	157	235	353	549	940	2115
$X (LG_1)$										
Panel 1	22,500	25,002	28,128	32,148	37,507	45,010	56,265	75,024	112,540	225,090
Panel 2	22,500	25,012	28,150	32,186	37,567	45,100	56,400	75,234	112,900	225,900
Panel 3	22,500	25,056	28,250	32,358	37,834	45,500	57,000	76,167	114,500	229,500
Panel 4	22,500	25,112	28,375	32,572	38,167	46,000	57,750	77,334	116,500	234,000
$X (LG_2)$										
Panel 1	0	2502	5628	9648	15,007	22,510	33,765	52,524	90,040	202,590
Panel 2	0	2512	5650	9686	15,067	22,600	33,900	52,734	90,400	203,400
Panel 3	0	2556	5750	9858	15,334	23,000	34,500	53,667	92,000	207,000
Panel 4	0	2612	5875	10,072	15,667	23,500	35,250	54,834	94,000	211,500

Note: P is the probability (10 represents 100% while 1 represents 10%), X is the payoff. The payoffs are rounded to the nearest ten and thousand. Source: authors' compilation.

Rice farmers who avoided risky decisions are more likely to choose from the first few rows (top five options), while risk neutral and risk loving subjects may prefer payoffs that are closer to the bottom (last five rows). Thus, the avoidance of zero earning by not picking higher rewards implies risk aversion. In other words, a DM with a uniformly concave utility function may choose extreme options, sure choices (with 100 per cent probability), while those with uniformly convex utility functions may choose the last or risky options (when the probability is 10 per cent). In addition, the lotteries expose subjects to the entire range of the probabilities and monetary rewards. In fact, a DM who avoids taking more risky options in the first and second panels of each treatment are attracted to risky decisions in the third and fourth panels which have relatively higher rewards. The choice of one (1) out of the ten (10) options in each panel results in sixteen (16) observations per subject. In other words, unlike most risk elicitation methods, the panel lotteries give four observations per treatment. Thus, different models were estimated for SG_1 , SG_2 , LG_1 ,

and LG_2 to observe/compare the heterogeneity in rice farmers' risk attitudes. The payoff associated with each probability in the SG_1 treatment is constructed using Equation (4).

$$\begin{aligned} EV_{ij}(SG_1) &= P_{ij}X_{ij} = C + (1 - P_{ij})t_j, \\ X_{ij}(SG_1) &= \frac{C + (1 - P_{ij})t_j}{P_{ij}} \end{aligned} \quad (4)$$

where $EV_{ij}(SG_1)$ is the expected value of SG_1 . $X_{ij}(SG_1)$ is the payoff associated with (SG_1). i varies from 1 to 10 corresponding to the lottery rows; j varies from 1 to 4, representing panels 1, 2, 3, and 4, respectively, P is the winning probability, which varies from 1 to 0.1, with 1 representing 100 per cent while 0.1 stands for 10 per cent. C is a constant fixed at N 225 for each of the panels in the SG_1 . This is the Naira equivalent of the 1 Euro used in the original S-GG lottery. Therefore, all the four panels under SG_1 began with a sure amount (225), which is responsible for a linear large increment in the expected values down the vertical rows. $t_j = 0.1, 1, 5, 10$ is a panel-specific risk premium corresponding to panels 1, 2, 3, and 4, respectively. The risk premium is responsible for the increment in the expected values as we move from panel one to panel four. Other treatments are calculated from the SG_1 . SG_2 is SG_1 less 225 ($SG_2 = SG_1 - 225$), as defined in Equation (5). On the other hand, LG_1 is a product of SG_1 and a constant, $LG_1 = SG_1 \times 100$, as defined in Equation (6). This is done to bring about a large increment in small gain one to examine the variation in subjects' risk attitudes. Lastly, LG_2 is expressed as LG_1 less than 22,500, ($LG_2 = LG_1 - 22,500$), as illustrated in Equation (7).

$$X_{ij}(SG_2) = X_{ij}(SG_1) - 225 \quad (5)$$

$$X_{ij}(LG_1) = (X_{ij}(SG_1))100 \quad (6)$$

$$X_{ij}(LG_2) = (X_{ij}(LG_1)) - 22,500 \quad (7)$$

Order of Presentation

A total number of 329 rice farmers were interviewed during the survey period with 328 fully completed questionnaires. All data were electronically collected using open data kit (ODK collect) with the aid of two smart android phones. This technology was used to record the GPS coordinates (latitude and longitude) of the locations of individual rice farmers. Notwithstanding the poor quality or absence of mobile networks in most villages, the locations (towns or villages) of each DM were manually recorded and later used to obtain the coordinates. Prior to the commencement of the survey, three postgraduate students were trained as research assistants on the use of the technology for data collection in late February 2016. The enumerators were also illustrated on how to fill in the record sheets. The record sheet used for visualising the lottery to farmers is presented in Figure 1.

Rice farmers were individually interviewed by contacting them at their homes and/or on their farms. In all cases, subjects' consents were sought before participating in the experiments/survey in line with the University of Reading regulations on research. In addition, respondents were informed about the voluntary participation and that they can withdraw from the experiment and survey at any stage. In all, no participant indicated interest in withdrawing from the experiments and survey. The risk experiment was conducted first, and lastly, questions were asked on the socio-economic factors. Respondents' minds were equally prepared for the need to use smart phones, because most farmers were not familiar with such technology for data collection. Subjects were presented first with the panel lotteries, starting from panel 1 to panel 4 of SG_1 , then SG_2 , LG_1 , and LG_2 , respectively. In addition, each DM was shown a bag containing 10 mixed blue and red balls, which represented the winning and losing probability. For the payment, only one of the panels in each treatment determined the earnings. However, this task was not incentivized for two reasons: first, due to the relatively high rewards involved, and second, it prevented non-rice farmers from participating in the experiment.











Row	Blue Balls=WIN, Red Balls=LOSE	Amount (N)	Choose 1
1	10 blue balls win 	225	
2	9 blue balls win 	251	
3	8 blue balls win 	282	
4	7 blue balls win 	322	
5	6 blue balls win 	376	
6	5 blue balls win 	451	
7	4 blue balls win 	563	
8	3 blue balls win 	751	
9	2 blue balls win 	1126	
10	1 blue ball win 	2251	

Figure 1. Record sheet for SG₁ panel 1.

- Instruction for small gain one and large gain one treatments

After the welcoming rice farmers with brief explanation on the importance of the survey, the experiments, and the likely impact of the study, the instructions for SG₁ were read to the farmers as follows: “The following 4 panels have 10 options each, the winning prize in each panel is the amount of Naira shown under the heading amount”. The blue balls represent the chances of winning; 10 blue balls imply one hundred per cent chances (sure), while 1 blue ball means a ten percent chance of winning a payoff (Figure 1). Conversely, the red balls imply a loss. The subject earned nothing if they did not win the lottery. The earning was determined by tossing a four-sided die. That is, any of the numbers 1, 2, 3, or 4 occurring from a toss of a four-sided die determines the payment panel. For instance, if a subject chose option 7, and one appeared during the die toss, they would win N 563 if any of the blue balls 1, 2, 3, or 4 was drawn from the bag, but nothing

if otherwise. Lastly, the record sheet was shown to the DM to make their choice. Similar instructions were given for LG_1 .

- Instruction for small gain two and large gain two treatments

The instructions for SG_2 were read as follows. “The following 4 panels have ten options each. The winning prize in each panel is the amount of Naira shown under the heading “amount”. The blue balls indicate the chances of winning; 10 blue balls imply hundred per cent chance (sure), while 1 blue ball means ten per cent chance. Conversely, the red balls imply loss. If you do not win the lottery, you will earn nothing or lose the sure amount. Your earning would be determined by tossing a die; any of the number 1, 2, 3, or 4 occurring from a toss of four-sided die determines the payment panel. For instance, chosen option seven and one appears during die toss earn you N 338 if any of the balls 1, 2, 3, or 4 is drawn from the bag. Kindly choose one option from each panel”. Then, the record sheet was given to the DM to make a choice. Similar instructions applied for LG_2 .

3. Results

The summary statistics of the variables included in the model are presented in Table 2. The average values suggest that rice farmers are risk avoidant with respect to SG_1 , SG_2 , LG_1 , and LG_2 , respectively. This is because the higher the probability values (the closer to 1) associated with the choices, the more averse an individual farmer is.

Table 2. Definition and Summary Statistics of the Variables used in the SAR Model.

Variables	Definition	Mean (SD)	Min	Max
SG_1	Small gain one probability index	0.80 (0.15)	0.10	1.00
SG_2	Small gain two probability index	0.60 (0.13)	0.10	1.00
LG_1	Large gain one probability index	0.70 (0.15)	0.10	1.00
LG_2	Large gain two probability index	0.60 (0.16)	0.10	1.00
Age	Age of the farmer in years	47.00 (12.50)	20.00	80.00
Education	Years of formal schooling	4.60 (4.50)	0.00	16.00
Male	1 if male, 0 if female	0.68	0.00	1.00
Christian	1 if Christian, 0 otherwise	0.56	0.00	1.00
Married	1 if married, 0 otherwise	0.94	0.00	1.00
Household size	Number of household members	6.00 (3.00)	1.00	21.00
Farm size	Rice farm area in hectares	1.90 (1.50)	0.20	16.00
Bad road	1 if farmers live in untarred, poorly accessible road areas, 0 otherwise	0.37	0.00	1.00

Source: authors' data analysis, 2017.

The sampled farmers are averagely aged (mean age is 47 years), which suggests that most of the farmers were in their productive age. The majority of the respondents did not complete primary education. Males constituted about 68 percent of the sample, with females constituting 32 percent. About 56 percent practiced Christianity as their religion, providing information on the representation of the two dominant religions in the country. Almost all (94 per cent) of the sampled farmers were married, and the average family size was 6 persons, which suggested financial responsibility for the household heads. An average farmer in the study sample cultivated 1.9 ha of land for rice production in the planting season preceding the survey year/period, while 37 percent lived in poor road network areas, an important infrastructural economic and sustainable development variable in our analysis.

The model results are presented in Table 3, respectively, for SG_1 , SG_2 , LG_1 , and LG_2 . The average values for each treatment were used in the analyses due to the high correlation between the panels within each treatment. The null hypotheses of the weak instruments were rejected, suggesting that the instrumental variables used were strong enough to obtain consistent estimates. The null hypotheses of the consistency of OLS were equally rejected in all of the risk models, implying that OLS may not yield consistent estimates. In addition, the Wald statistic, which was significantly different from zero for all the treatment models,

attested to the overall goodness of fit of the models. The results corresponding to the 60 km are reported for SG_1 , SG_2 , LG_1 , and LG_2 , respectively, in line with [28,29], who reported a spatial dependence limit.

Table 3. The Effect of Spatial Dependence on Rice Farmers' Risk Preferences.

Variables	SG_1	SG_2	LG_1	LG_2
Spatial Dependence				
Spatial lag	0.0016 *** (0.0002)	0.0019 *** (0.0002)	0.0019 *** (0.0002)	0.0019 *** (0.0002)
Farm- and Farmer-Specific Factors				
Age	0.0032 *** (0.0009)	0.0021 *** (0.0008)	0.0022 ** (0.0010)	0.0019 ** (0.0008)
Education	0.0043 (0.0025)	0.0002 (0.0025)	0.0035 (0.0026)	0.0037 (0.0024)
Christian	0.0498 ** (0.0217)	0.0498 *** (0.0185)	−0.0263 (0.0207)	0.0217 (0.0191)
Household size	0.0021 (0.0031)	0.0027 (0.0034)	0.0016 (0.0034)	0.0004 (0.0037)
Farm size	−0.0163 ** (0.0075)	−0.0047 (0.0056)	−0.0155 * (0.0081)	−0.0074 (0.0069)
Male	0.0559 ** (0.0234)	0.0498 *** (0.0196)	0.0616 *** (0.0217)	0.0580 *** (0.0210)
Married	0.3103 *** (0.0611)	0.2214 *** (0.0556)	0.3089 *** (0.0587)	0.2137 *** (0.0509)
Location/Infrastructure				
Bad roads	0.1097 *** (0.0206)	0.0549 *** (0.0186)	0.1123 *** (0.0208)	0.0595 *** (0.0195)

Source: authors' data analysis, 2017. N = 328, ***, **, * respectively represent coefficients are significantly different from zero at 1%, 5% and 10%. Standard errors are in parentheses; diagnosis statistics: weak instruments: $SG_1 = 30,562.80$ ($p < 0.00$), $SG_2 = 23,621.55$ ($p < 0.00$), $LG_1 = 25,382.5$ ($p < 0.00$), LL = 18,951.71 ($p < 0.00$); OLS consistency: $SG_1 = 29.15$ ($p = 0.00$), $SG_2 = 57.88$ ($p = 0.00$), $LG_1 = 71.4$ ($p = 0.00$), LL = 36.59 ($p = 0.00$); Wald Tests: $SG_1 = 787.9$ ($p < 0.00$), $SG_2 = 753.4$ ($p < 0.00$), $LG_1 = 738$ ($p < 0.00$), $LG_2 = 492.9$ ($p < 0.00$).

Factors that significantly explain risk attitudes (SG_1) include age, religion, farm size, gender, marital status, bad roads, and spatial dependence, while age, religion, gender, marital status, bad roads, and spatial dependence significantly determined attitudes towards SG_2 . Similarly, age, farm size, gender, marital status, bad roads, and spatial dependence were the determining factors for attitudes toward LG_1 , while attitudes toward LG_2 were significantly explained by age, gender, marital status, bad roads, and spatial dependence. Note that the positive coefficients imply risk avoidance (risk aversion).

Willingness to take risks was spatially determined, as indicated by the significant coefficients of all the spatial lags in all of the risk treatments (Table 3). Similar studies observed the spatial parameter and reported that rho increases up to a particular distance, and later decreases [18,54]. We observed a similar pattern, with 60 km constituting the limit of spatial dependence. In short, statistical significance of rho suggests the existence of neighbourhood effects in risky decision making.

Accordingly, with respect to SG_1 , a farmer's risk avoidance is positively associated with an increase in the distance weighted sum of all neighbors' SG_1 . Taking the average neighbour's SG_1 for each farmer, we found that an increase in the average neighbour's SG_1 (i.e., risk avoidance, note that values are between 0 and 1) of 0.1 would mean an increase of 32.8 on the distance weighted sum of all neighbour's SG_1 , $0.1 \times 328 = 32.8$. This means that an increase in the farmer's own SG_1 (risk avoidance) of 0.05 units ($32.8 \times 0.0016 = 0.05$).

The effect of a farmer's neighbours SG_2 , LG_1 , and LG_2 on their own SG_2 , LG_1 , and LG_2 was 0.06 for each, respectively. Older rice farmers avoided risk taking or were more risk averse relative to the younger farmers. The results also revealed that farmers practicing Christianity tended to avoid risk taking with respect to small stakes compared to Muslims and others. Small land holders were less willing to take risk relative to large-scale farmers, suggesting that increasing farm size might lead to taking risky decisions. For instance, an increase of 1 ha would lead to a decrease in SG_1 of 0.016 units. Male rice farmers were less likely to take risk compared to their female counterparts. Married farmers showed less willingness to take risks relative to singles. The results also showed that farmers living in the un-tarred bad road network areas were less willing to take risky decisions compared to those living in more accessible road areas. The directions of some of the variables and the results are therefore consistent with the expectations while others differ from previously expressed views on risk attitudes.

4. Discussion

The results show that unobserved spatial heterogeneity is associated with farmers' risk preferences. Although we cannot identify what exactly the heterogeneity is, by incorporating spatial dependency in the farmer's risk preference model, we can control for these spatially dependent effects (e.g., soil, topography, farmers emulating each other). It follows that given the observed socio-economic variables, farmers' risky behaviour is influenced by unobserved spatial attributes. Put differently, the closer the distance between the farmers, the more likely they would behave in a similar manner. This is plausible as it may reflect the geographical relationship as well as socio-economic conditions between and among individual rice farmers. For instance, farmers in Nigeria may exhibit similar behaviour, which may differ from their counterparts in Ghana, due largely to the different regional characteristics (e.g., soil, topography, climate, culture). In summary, our finding upholds the principle of proximity in similar patterns of attitudes and therefore agrees with Tobler [55], who posited that closer observations and individuals tend to behave in similar manners compared to distant ones; with important implications in sustainability and sustainable development.

Informal communication and interaction are common phenomena in both the urban and rural areas of most developing countries due largely to clustering. The revelation here shows that rice farmers are related in some ways climatically, geographically, economically, socially, culturally, and ecologically. This agrees with [5], and suggests that farmers living closely may behave similarly relative to distant ones. Evidence of spatial dependence may be reflected in decisions to adopt improved agricultural technology, as well as decisions relating to other investment opportunities. In fact, the adoption and diffusion of technological agricultural innovation may be accelerated or ride on the back of the information possessed by farmers' neighbours. Such geographical influences are often ignored by economic policy. In the study area, farmers share many personal and formal attributes/factors such as farm holdings, land use policy, educational institutions, and roads, as well as uncontrollable factors such as the weather and climate. It suggests that observed patterns of behaviours should not only be important for local interaction and interpersonal communication, but also instrumental in the decision-making processes with respect to local, national, and international agricultural policies. Furthermore, the degree of heterogeneity in risk attitudes is a complex process involving many uncontrolled variables. This makes incorporating spatial dependence in farmers' risk preferences important in controlling for these unobserved factors, which may vary from farmers' and farms' characteristics to institutional factors. Additionally, risk attitudes have found applications in different aspects of life such as health, finance, sports, and education. The use of education as an instrumental variable suggests that this variable is not only important in general economic policy, but also specifically key to farmers' spatial heterogeneous risky behavior. Such spatial attributes depict the universality of education irrespective of the geographical locations or place of residence of individuals. In short, there is evidence of

spatial dependence in risky behaviour among the sampled farmers, an important novelty and revelation for policy in the field of agricultural and applied economics.

The finding supports previous findings, which reported a negative correlation between age and risk aversion [10,40]. It is, however, contrary to some findings that risk aversion decreases with age [9,15]. Older rice farmers may be less interested in taking up risky and productive investments due to their perceived old age. They may have a strong desire and expectation for enjoyment, being willing to enjoy the goodness of life since death is inevitable. On the contrary, the desire to invest in the youth for higher future outcomes and economic benefits may constitute a push factor for younger rice farmers who show more willingness to take risky decisions.

Although it may be difficult to infer how religious an individual is, the results indicate that Christians statistically and significantly behave differently by showing less willingness to taking risky decisions compared to others. This may partly and probably due to the small amount associated with the small stake lotteries. On the other hands, it may reflect attitudes toward certainty since a bird in hand worth more than hundred birds in the bush. Past studies have reported that religious farmers are risk averse [10,37]. Religion may drive farmers' beliefs as well as influencing their level of gambling and day-to-day activities, including investment decisions. Notwithstanding, politics may contribute to the preferences revealed by the subjects, and subsequently, farm decisions. In summary, the results confirm the heterogeneity of risk attitudes across religions. Farmers' risk preferences were correlated with farm size. More specifically, farmers who were risk averse were associated with small farms. This result is consistent with the expectation and previously reported finding [6]. There are two possible reasons for this finding. On one hand, small-scale farmers may require a significant amount of income to expand their scope of operation, which may make them reticent to taking risk. On the other hand, large farms may imply additional financial commitments, thus taking risks might be adoptable strategies for increasing farm income. If farm size is a proxy for wealth or income, it is safe to conclude that the result agrees with previous findings reporting the tendency of less risk aversion among wealthier farmers [5,6,8,10,37,40].

Male farmers were found to be more risk averse than female farmers. The result presents a contrary view to the previously reported findings that males are risk takers [49]. It is also opposed to the previous findings that female farmers are more averse to risk taking than their male counterparts [16,37,47]. More so, it disagrees with previously expressed views of financial risk behaviour that women are less financially tolerant and more financially risk averse compared to men [42–44]. It also disagrees with Harris, Jenkins and Glaser [45], who attributed gender differences in perceptions about outcomes and risk taking to low propensity in enjoyment among the women compared to men. Additionally, male rice farmers may perceive lotteries as liquidity capital compared to female farmers, who may attach more value to the monetary rewards offered by the lotteries. This proposition is based on the fact that, on average, male rice farmers cultivate more land for rice production compared to female farmers, indicating more income from farming. In addition, women tend to have higher expectations for social engagements and activities, which may drive their desire and willingness towards taking risk, irrespective of the size of the stake. Farmers' attitudes may also be viewed from the fact that males may have a strong attachment to the status quo or endowment effect; that is, not willing to lose the 'certain' yield from the traditional technology or be less willing to pay a price for the 'uncertain' yet higher yield from the improved technology.

Our finding indicate married rice farmers avoided risk taking compared to single rice farmers. As earlier noted, single individuals tend to view loss from a different perspective compared to the married individuals who may perceive a loss as a threat to livelihood due to additional family responsibility and financial commitments. Indeed, married farmers' avoidance of risk taking may be attributed to a fear of a loss of money. This is also in agreement with the popular saying that a bird in the hand is better than two in the bush, since married individuals have more pressing financial concerns and would probably do

everything within their capacity to avoid losing money. Arguably, married farmers are expected to show more desire to take risks as an option for gaining more money to cater for their family's financial needs but our results show contrary which calls for policy concerns in relation to family size.

In both developed and developing countries, rural areas generally lack access to infrastructural facilities compared to urban areas. Bad road networks may limit movement and access to information and the market, thereby limiting the production and income potential of farmers residing in rural areas. It can therefore influence farmers' behaviour or attitudes during decision making processes. Additionally, country side including peri-urban areas are associated with low economic activities but dominated by agrarian economy. Furthermore, rural areas are often associated with poverty attributable to lack of access to social amenities and infrastructural facilities. Our result shows that poor road network, occasioned by poor infrastructure and low income influence low interest in risk taking. It is therefore aligns with past studies, which found poor farmers were more averse to risk taking [5,8,56]. Since roads are important infrastructure and economic development variables, it shows that this finding agrees with Harrison, Humphrey and Verschoor [9], who revealed that farmers living in low rainfall areas in Uganda showed a higher aversion to risk, on average, than farmers living in five other agro-climatic areas with relatively higher rainfall distribution.

The finding also aligns with those that attributed higher risk aversion to income variability [57,58]. Furthermore, farmers' risk aversion was reportedly negatively related to willingness to pay/adopt improved agricultural technology that may bring about sustainable intensification in East Africa [59]. This underscores the economic importance of risk aversion or risk avoidance in different aspects of economics including demand for improved farm practices, and in our case infrastructure facility. Infrastructure aids food supply and demand and thus constitutes push factor in the food supply chain. The revelation here may also be decoded as low tendency for risk taking in the rural areas is attributable to the less risky rural environment relative to the urban environment. In short, access to a good road network significantly explains farmers' risk aversion behaviour in the study area, the implications of which may be applied at national and regional levels. It therefore buttress the importance of road infrastructure not only in economic behavior but also in sustainability and sustainable development as it aids and accelerate economic growth through ease of movement of farm produce as well as other economic goods and services especially from the rural areas to the urban markets where farmers stand a better chance of earning higher profits

5. Conclusions

We provide insights into the role of unobserved spatial heterogeneity in explaining risk preferences among rice farmers in Nigeria by incorporating spatial dependency in a farmer's risk preference model.

We found that incorporating a spatial dependency term into farmers' risk preference models (i.e., SAR) can help to control for unobserved spatial heterogeneity in farmers' preferences. Although this type of heterogeneity is not observable and we cannot identify its source, controlling for it is important to avoid bias in the model coefficient estimates [30,31]. The non-observability of the spatial heterogeneity comes from the common lack of information on spatially dependent factors such as soil, topographic, climatic, and socio-economic conditions present in an area. Although there may be cases where some of this information may be available for the researcher (e.g., rainfall data), other types of information are rarely collected (e.g., whether farmers emulate each other or share information).

We found famers' risk preference heterogeneity due to their socio-demographic characteristics, such as age, gender, religion, and marital status; farm characteristics such as farm size; and local infrastructure (bad roads).

Our results may have important implications for policy design. Both observed and unobserved spatial heterogeneity may affect farmers' risk preferences and therefore farm-

ers' decision-making processes especially relating to sustainable farm practices, sustainable intensification and subsequently sustainable development. Policies aiming to achieve sustainable development and food security usually involve some type of intervention (e.g., the promotion of a farmer's adoption of agricultural practices and technologies that contribute to achieving these objectives). Farmers' decisions to engage with these policy intervention programmes may depend on their risk preferences. Hence, in order to maximize the net benefits associated with these programmes, the design of farmers' engagement and behavioral factors seems crucial. Such design may require having different streams of action to account for observed and unobserved spatial heterogeneity in farmers' risk preferences. For instance, when promoting the adoption of new technologies in a region/country, there is a need to identify whether there are any socio-demographic, economic, or geographically determined conditions that may affect farmers' risk perceptions, which will eventually determine their decisions to adopt or not new technologies or improved farm practices that would enhance farm sustainability.

In the case that these exist, new technology adoption can be optimized by focusing the efforts into those characteristics and locations where farmers are less likely to be risk averse (i.e., more prone to engage with policy programmes). This means that specific interventions to more risk averse farmers may need to be designed to persuade farmers to change their perceptions and to adopt risky economic activities (e.g., adopting new technologies). However, the latter would only be economically viable if the expected benefits of the intervention are higher than the costs. Hence, both observed and unobserved spatial heterogeneity in risky decision making should be given special attention in the design and formulation of economic policies and programs that would improve the living conditions of rice farmers, especially in rural areas. Likewise, our results suggest that policies aiming at infrastructure improvement (e.g., road networks in the rural areas), which is associated with farmers being relatively less risk averse, may facilitate farmers engagement in policy programmes (e.g., adopting new technologies, sustainable agricultural practices). Good and accessible roads will not only increase farmers' level of awareness or information on improved agricultural technology, but also increase the chances of transporting and marketing farm produce at urban and international markets for farmers' economic benefits.

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